Navigating the Deep

The Path to Underwater Autonomy **by 2030**

PRESCOUTER 2023

While autonomous underwater platforms are certainly advancing and embracing AI engines, the journey towards complete autonomy is far from complete. Current technical limitations and capabilities pose challenges that must be addressed taking a holistic approach.

High costs to obtain labeled data

AI systems require hundreds of TBs of data for task execution. Acquiring and labeling this data is costly and time-consuming, with image labeling averaging $2.50/image and potentially hundreds of thousands of images needed to enhance capabilities. Moreover, collecting and using SONAR data more applicable to underwater environments is difficult and the state of the art has not identified approaches to overcome severe limitations such as overdrifting, noise, and the presence of shadows.

Need a minimum investment of

$5M - $10M

to update training data applicable to underwater environments, namely label image data, which does not take into account the cost of collecting this data and leveraging more applicable data (e.g. SONAR) in the first place.

$100M

To advance the current best-performing state of the art platforms to a fully autonomous platform, according to experts interviewed by PreScouter.

Two key gaps are addressing "noisy" data and boosting latencies **by 30X**.

Navigating AI challenges in aquatic environments

Water interferes with electromagnetic wave propagation, leading to signal disruption. It's essential to improve communication protocols, boost bandwidth, reduce latency to less than 10 ms (compared to 300-400 ms in autonomous cars), and ensure signal robustness for efficient communication among different entities.

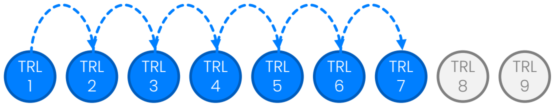
Bridging architectural and latency hurdles

High-level autonomous systems need to manage data with significant noise and uncertainty. Hence, there's a pressing need to enhance system latencies by 30x.

1. *Trillions of operations per second - a key metric to measure chip performance;* 2. *Based on EdgeCortix Sakura1 performance.* Source.; 3. *Technology readiness level;* 4. Valencian Research Institute for Artificial Intelligence. Source.

Continuous advancements in hardware will boost the processing capabilities of underwater AI engines.

To achieve continuous autonomy, models need a minimum of 7 TRLs improvement.



Better performing autonomous architectures and edge computing are crucial

Achieving 1000 TOPS[1] for full autonomy necessitates 25 top-tier edge computing chips in a unified architecture. Addressing computational hardware concerns is vital for real-time data processing. This requires improved sensor tech and adoption of tools like FPGAs. Merging deep learning with SONAR and integrating edge computing can overcome latency issues and maximize platform potential.

Full autonomy is still elusive

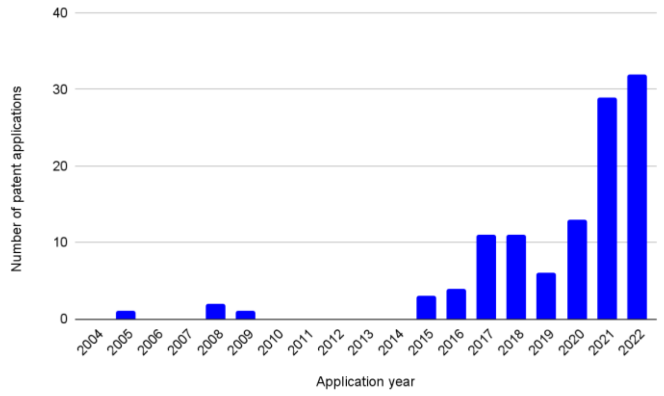
To achieve continuous autonomy, models need a minimum of 7 TRLs improvement. Despite advances like YOLO v5 and Mask R-CNN, and methods like NASA's Jet Propulsion Lab's Model-Driven Engineering and domain-specific languages (DSLs), achieving real-world full autonomy demands a 7 TRLs leap, as per VRAIN's analysis.

1. *Trillions of operations per second - a key metric to measure chip performance; 2. Based on EdgeCortix Sakura1 performance.* Source.;
3. *Technology readiness level;* 4. Valencian Research Institute for Artificial Intelligence. Source.

Progress in achieving autonomy for underwater platforms is still in its nascent stages, though these gaps are being addressed by leading players globally. In order to meet the needs of commercial and defense entities around the world and reach full autonomy, further R&D is required and key players like NVIDIA are already focusing their attention on this need.

A 10x increase in patent applications for underwater autonomy/AI in the last 7 years

Underwater autonomy is on the rise, as indicated by our IP analysis. This expansion of the IP domain includes diverse applications like surveillance, unmanned vehicles, and advanced sensors. Advancements in specialized chips and neural networks are key for achieving autonomy.



The path forward: the next 5 years

Autonomous Launch & Docking

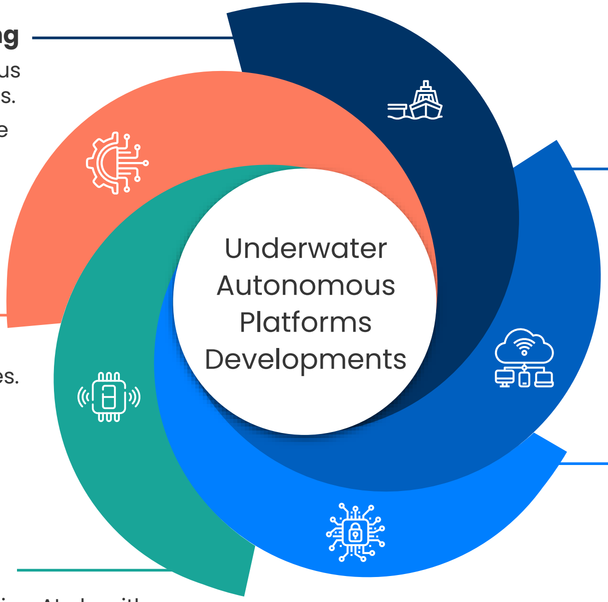
- Increasing focus on autonomous launch and docking capabilities.
- Expected to significantly reduce operational costs.

Engine Evolution

- Limited potential for new developments in electrical engines.

AI enhancements

- Focus on enhancing AI algorithms, particularly for sensors.



Cloud-Enabled Communication

- Enabling AUVs to communicate with surface vehicles.
- Accessing cloud resources for enhanced data collection.
- Reducing the need for direct UUV-to-cloud connections.

Cybersecurity Emphasis

- Anticipating increased attention to UUV cybersecurity.
- An upcoming area of disruption in the industry.

What's covered in this report

DIVE DEEPER: In this Intelligence Brief, we offer insights into artificial engines applicable to underwater platform autonomy. We explore limitations, tools, examples, and data enhancement. Additionally, we identify overarching trends in robotics and autonomy R&D, emphasizing the potential contributions of autonomous underwater platforms across various industries, including the military sector.

Recognize limits and needs for underwater vehicle AI autonomy.

Highlight tools and datasets for functional AI engine development.

Showcase tangible real-world advancements in this domain.

TOWARDS AUTONOMY

Strategies to create or enhance datasets for vital AI engine autonomy functions.

Contents

LIMITATIONS AND REQUIREMENTS

Recognizing the limits and needs for underwater vehicle AI autonomy.

Strategy for developing a fully autonomous underwater platform

- Leverage and augment existing platforms **instead of starting from scratch** to minimize investment and time required (using this approach will require an estimated **$100M in R&D costs**, according to PreScouter experts)
- This is a complex effort that **will require** a company or group of **stakeholders with expertise** in numerous technical areas, including
  - navigation accuracy
  - dealing with water drift
  - sensor integration
  - electrical integration
  - AI and software integration
  - resolving mechanical issues
- **Work** with **or recruit SONAR experts**, due to lack of SONAR data for training
- **Collect/simulate SONAR data for the geographies and environments** in which your platform will be expected to operate autonomously, as data for underwater environments in Europe will look different from those in the Americas or Asia.

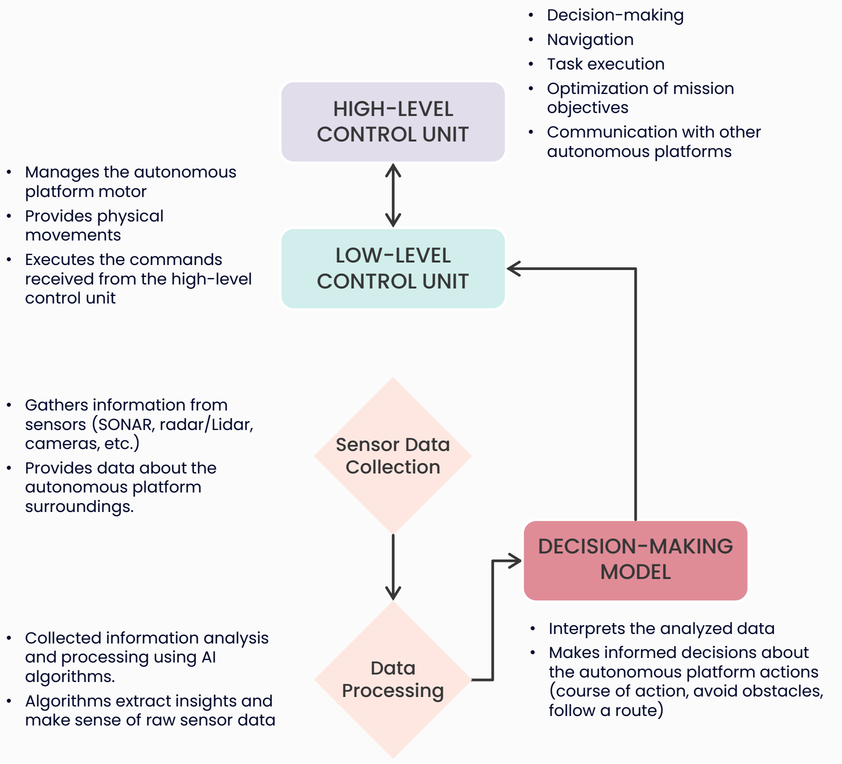


Figure. This diagram outlines the key components for achieving autonomous underwater operation with AI and sensor data. It includes High-Level Control, Low-Level Control, Sensor Data Collection, Data Processing, and a feedback loop for real-time adjustments. Source: Anonymous SMEs

Limitations found during the development of Autonomous Underwater Platforms

Lack of Data

Training AI engines for complex tasks like object detection takes time due to the need for extensive data. In underwater environments, data collection challenges arise due to harsh conditions introducing noise and interference.

Complexity

Implementing AI engines, particularly with limited computing and cloud access is complex. Sensor data handling and processing remain as the most complex unresolved tasks to achieve.

Cost

Developing and deploying AI engines is expensive cost includes R&D, specialized hardware and sensor components, communication equipments, power sources, etc.).

Time

Training AI engines for complex tasks takes time due to the need for extensive data. In underwater environments, data collection challenges arise due to harsh conditions.

Limitations found during the development of Autonomous Underwater Platforms

Labeled vs unlabeled Data

Training AI with labeled data (correctly tagged) is costly; using unlabeled data requires implicit output identification. Current efforts are addressing via unsupervised data processing.

Environmental heterogeneity

AUVs operate in diverse environments, making training AI engines to perform well across all conditions challenging. The heterogeneity varies with the purpose of use, type of environment (e.g., freshwater, marine environments, depths).

Different sensor requiring ML processing

AUVs use various sensors (cameras, sonar, radar), complicating AI training for effective multi-sensor utilization and logical coordination and interpretation by AI engines.

Number of Stakeholders

AUV autonomy involves varied stakeholders, hindering AI consensus. Limited collaboration among Research Institutions, industry partners, engineering, and design experts adds complexity.

The progress of autonomous underwater platforms faces long-term developmental limitations.

ROADBLOCKS

Underwater sensors are limited in range, resolution, and visibility, and need to deal with high noise/ uncertainty levels, which makes it difficult for AI systems to process and interpret data.

Communication protocols must enhance bandwidth, reduce latency, and bolster signal robustness for underwater autonomy.

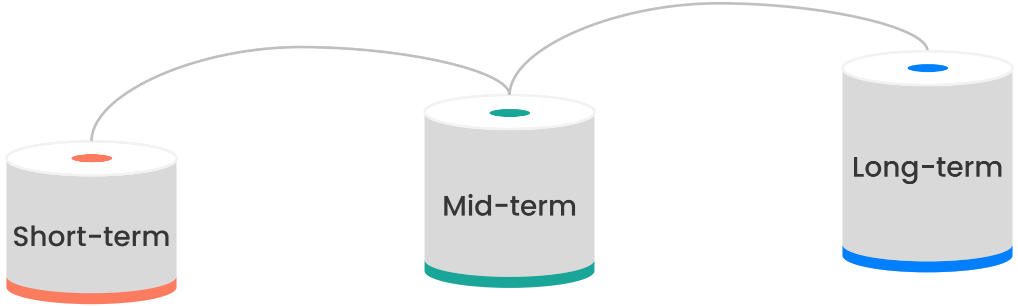
Deep learning needs labeled data, which is challenging and time-consuming to gather.

Enhancing underwater mapping using diverse sensor methods and innovative strategies can enable real-time spatial awareness updates for AI navigation.

AI must adapt to real-time decisions to navigate underwater obstacles, complex terrain, and varied environmental conditions (currents, temperature, pressure, visibility).

Maintaining AI systems for prolonged periods in remote underwater locations presents intricate engineering challenges for ensuring reliability and upkeep.

Design AI systems which can adapt and learn to previously unexplored or rapidly changing environments.

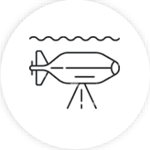


EXPECTED CAPABILITIES

	Short-term	Mid-term	Long-term
Autonomy perception	Systems grasp object and event connections in space and time.	Computer vision algorithms predict real-time future actions and locations from past behavior.	Systems learn and adapt in real time, forming hypotheses about the world and refining their models.
Decision making	Systems enabled to select actions using machine learning to improve decision making.	Multi-agent systems can be used to coordinate the actions of large numbers of agents to solve complex problems.	Systems reason across extended periods of time spanning years. It will require more abstract reasoning capabilities.

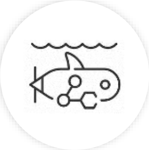
PRESCOUTER

Identifying gaps in achieving underwater platforms autonomy



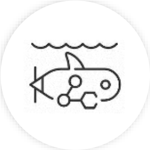
CURRENT FUNCTIONALITIES

Control	AI engine	Processing
Navigation	Mapping Algorithms	Use of sensor data
Object Detection	Computer Vision (CNNs)	Locate common objects
Classification	ML Algorithms	Categorize common objects
Mapping	Data Processing Algorithms	Data & create 2D-3D maps
Path Planning	Optimization Algorithm	Optimize routes



EXPECTED FUNCTIONALITIES

Control	Capability	GAPS
Situational Awareness	Merge detected objects Time synchronization Integrate sensors data	Auto detect & identify surface and underwater targets
Dependable Performance	Train recognition models Improved device reliability	Anomaly prediction, Self-diagnosis, Troubleshooting, Functional continuity.
Navigation	Limited communication rerouting Detect underwater objects Adapt to environment	Self Route Set, Avoidance, Autoship Steering, Self position estimation.
Mission	Balance control algorithm Learning from events Collaboration/Mission execution	Attitude Control & estimation, Action assessment, Decision-making, Collaborative control.



FULLY AUTONOMOUS PLATFORM

OUTCOME: Enables autonomous decision making on-the-fly to reach overall objectives, determines self-response for issue prevention & handling, allowing extended missions with no human intervention.

Current state of the art in achieving underwater autonomy

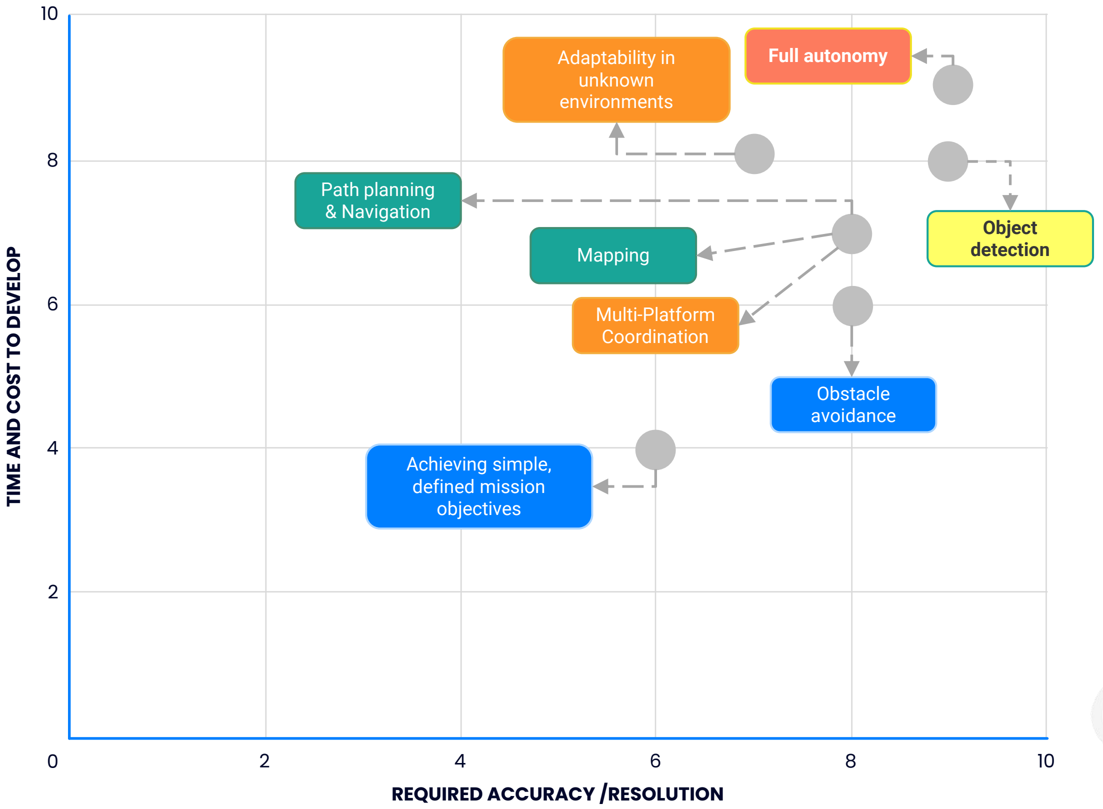


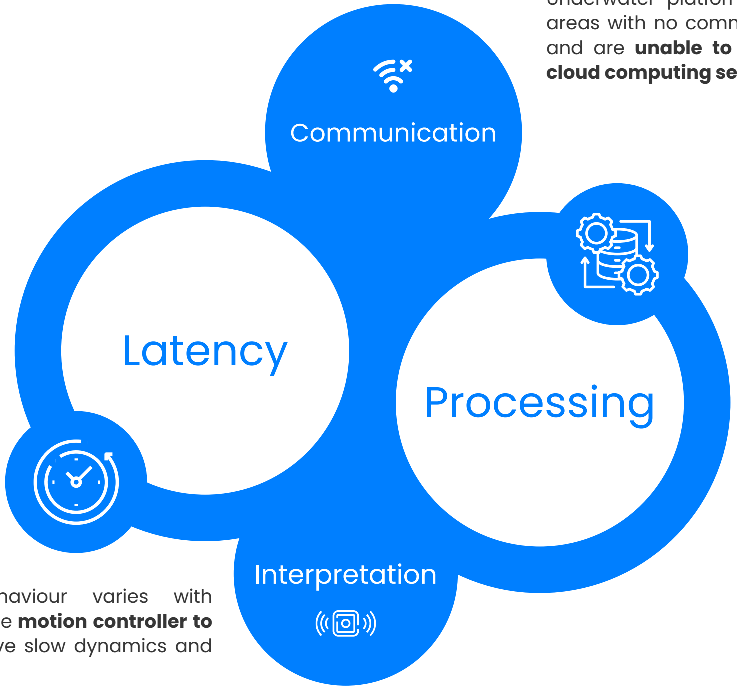
Figure. Analysis of the elements required to achieve underwater autonomy based in their current state of the art, functionalities, cost, and technology readiness level (TRL).

The TRLs show that various **technological aspects** of underwater platform development have progressed from **conceptual stages** (TRL 3) through **component validations** (TRL 4) and the **creation of functional prototypes** (TRL 6 and 7). TRL 7, denoting operational testing, marks **significant progress** towards practical application. However, the **SME analysis**, **considering the time and costs** required to achieve **full autonomy** in terms of **accuracy and resolution**, suggests that we still have a **considerable distance to go**.

Full autonomy is currently limited by latency, processing power, and autonomous architectural limits

Communication will not be essential for fully autonomous platforms, except when coordinating among multiple platforms.

Progressing from recognition to cognition to judgment and control necessitates the collection of data from sensors, the transmission of this data to processing centers via interfaces (buses), and subsequently sending it to actuators and other low-level control mechanisms through separate interfaces. With each step having distinct latencies, **these cumulative delays contribute to an overall latency requirement that can pose challenges for AUVs in making real-time decisions. Experts assess millisecond latency requirements for sensor data collection and processing, and second latency requirements for high level controls and communications**.



Underwater platforms often operate in areas with no communication networks, and are **unable to take advantage of cloud computing services**.

Autonomous platforms must be able to process large amounts of data, communicate with other devices, and connect to communication networks. **Higher level control functionalities will require more complex autonomous architectures that will require even more processing power**. Each hour of mission will require collecting and processing 1 gigabyte (GB) of data from synthetic aperture sonar sensors alone, and about 20 GB for all sensors from state of the art platforms available today.

The dynamic behaviour varies with payload, requiring the **motion controller to adapt**. Thrusters have slow dynamics and control rates.

Interpretation is limited by processing power and autonomous architectures.

As a reference point, in EVs today, the computing power required for each level of self-driving vehicle is generally held to be as follows: less than 10 TOPS for L2, 30 to 60 TOPS for L3, more than 100 TOPS for L4, and predictions of around 1,000 TOPS for L5. Existing platforms are only capable of meeting some requirements of L3 and L4 autonomy. Source.

Identifying latency requirements depends on autonomous functional and physical architectural choices

Autonomous architecture from MIT, though defined for an autonomous car, illustrates how to determine latency requirements for **any autonomous platform**.

- The **influence between functional and architectural choices** is also highlighted and helps illustrate the need for computational resources.
- Without the need for safety required for autonomous vehicles, **current latency achievable** in platforms stands at **~320ms**.

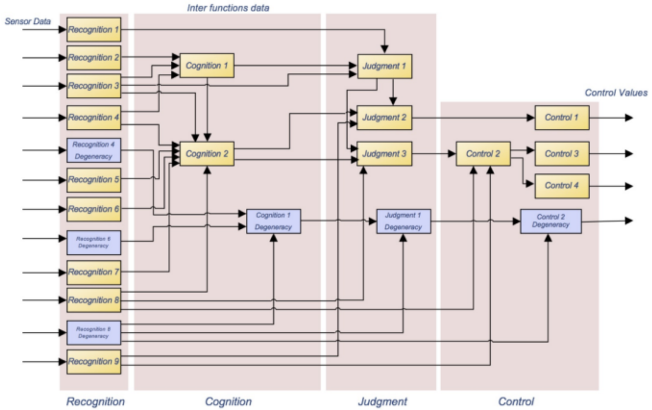


Figure 1. Example of a functional architecture for an autonomous platform (blue tasks are degeneracy equivalents of some yellows tasks) to improve safety through redundancy. Source: MIT

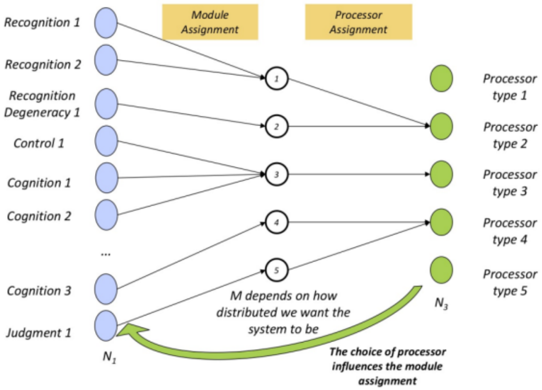


Figure 2. Link between functional and physical architecture choices. Source: MIT

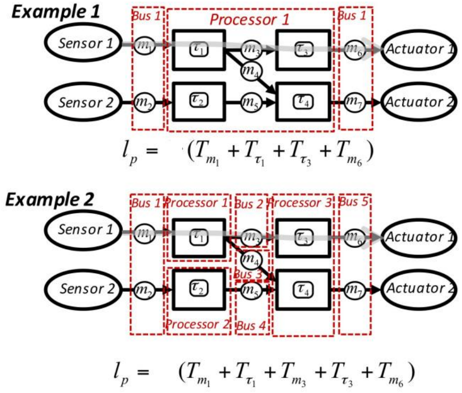


Figure 3. Example of latency calculations for two different architectures. The latency is calculated for the path between Sensor 1 and Actuator 1 in both cases. Adding a bus adds latency to the message going from task T1 to T3. To ease the notation in the figure, messages are here designated with their own index, as opposed to the tasks they are linking, in the equations above; m3 would be designated as T1T3 in the provided latency formula. Source: MIT

Cloud computing is not a realistic option for underwater platforms, especially if you're not planning to use expensive wideband satellite communication. The key to effective processing is edge computation, and it's essential to have the necessary hardware onboard.

Today, technologies like GPUs, such as NVIDIA's GPUs, or even more powerful hardware like the A100 GPU, are the types of hardware you need to handle the significant volume of data processing required in real-time underwater scenarios. Without this kind of dedicated hardware, attempting to process such data externally or in the cloud is not a viable solution.

Anonymous Interviewed Expert

Presently, achieving underwater autonomy relies on internet and cloud connections. Edge computing could remove this necessity, advancing us toward complete underwater autonomy.

EDGE COMPUTING

Edge computing is anticipated to supplant cloud-based DL computation, providing **distributed, low-latency, dependable intelligent services.**

Autonomous underwater platforms can represent model systems designed to **overcome latency challenges by using edge computing in an IoT gateway.**[1-2]

A **Python-based algorithm** was developed to **communicate autonomously** with underwater sensors, actuators, and controller, and the cloud computer vision APIs

The system is **effective and features the asset of combining an AUV with deep learning cloud services for processing and analyzing photos.**

A **hybrid cloud/edge architecture** is recommended to **ensure a real-time control** loop and achieve consistent results today.

** Deep Learning*

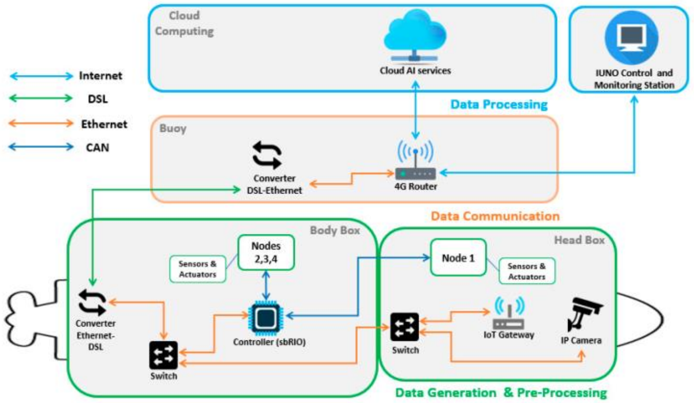


Figure. The physical layer is constituted by a variety of electronic devices interconnected by three different networks according to their functionality: the CAN (controller area network), the Ethernet network and Internet/cloud network. The CAN network is composed of four slave nodes and one master. Each node consists of an electronic card specifically designed for this vehicle and its assigned tasks, and has as a core a PIC18F4685 microcontroller, working at a frequency of 25 MHz. The AUV operated at 200 m depth. Source: Salhaoui *et al.* 2020.

Comparing hardware platforms able to support autonomy of underwater platforms.

24 TOPS/WATTS

CPUs are flexible but inefficient, require additional operations for each useful algorithm operation, which slows down computation and increases power consumption

CPU

GPUs are faster for parallel tasks, but CPUs are more versatile.

GPU

FPGAs are reprogrammable chips, **more efficient and powerful than CPUs and GPUs**. Ideal for applications where performance and flexibility are critical.

FPGAs

ASICs are specialized chips that are very efficient for a specific problem, but expensive and limited in use.

ASICs

Flexibility and Ease of Use

Performance & Power Efficiency

Control	CPU	GPU	FPGA
Input Processing	1	1.79×	1.41×
Image Arithmetic	1	3.19×	2.93×
Image Filters	1	3.17×	3.89×
Image Analysis	1	2.34×	5.67×
Geometric Transform	1	10.3×	16.6×
Features/ OF/ StereoBM	1	7.44×	22.3×

Table. The energy/frame reduction ratio (how much energy can be saved per frame when using a hardware accelerator instead of a CPU). A higher ratio means that the hardware accelerator is more efficient and can save more energy. Source

Up to 196x compared to normalized CPU values

Figure. Comparing hardware platforms for AUVs defined by their flexibility and ease of use vs performance and power efficiency. CPU: Central processing unit. GPU: Graphics processing unit. FPGA: Field-programmable gate array. ASIC: Application-specific integrated circuit. Source: Siek *et al.* 2023.

Relevant FPGA developments

intel.

FPGAs

PROS

- Capable of real-time data processing, ideal for time-sensitive applications.
- Applied in signal processing, video/audio equipment, and data transfer.
- In AI, their flexibility and performance-to-power ratio suit dynamic applications.

CONS

- Intricate development; it requires deep digital logic understanding due to hardware-level programmability.
- Limited machine learning libraries for FPGAs complicate FPGA-based AI development.

Fuzzy PID algorithms ensure controlled yields, enhancing further the accuracy and reduced response time.

	Intel Agilex® 9 FPGAs Direct RF-Series	Intel Agilex® 7 FPGAs F-Series / I-Series / M-Series	Intel Agilex® 5 FPGAs E-Series / D-Series	Intel Agilex® 3 FPGAs
Logic Capacity Range (logic elements)	1.4M – 2.7M	573k – 4M	50k – 656k	Coming Soon
Memory (Max)	287 Mb	485 Mb (32 GB HBM2e option)	69 Mb	
DSP Type	Variable-Precision DSP Blocks	Variable-Precision DSP Blocks	Enhanced DSP with AI Tensor Blocks	
18x19 Multipliers (Max)	17,056	25,584	3,680	
Hard Processor Options	Quad-Core Arm Cortex-A53	Quad-Core Arm Cortex-A53	Dual-Core Arm Cortex-A76 Dual-Core Arm Cortex-A55	
High-Speed Interfaces (max data rate)	58 Gbps XCVRs 64 Gsps ADC/DAC	116 Gbps XCVRs	28 Gbps XCVRs	
Processor Interfaces	PCIe 4.0	PCIe 4.0/5.0, CXL	PCIe 4.0	
Memory Interfaces	DDR4, QDR IV	DDR4/5, LPDDR5, QDR IV	DDR4/5, LPDDR4/5, QDR IV	
I/O Count (Max)	660	768	444	
XCVR count (Max)	32	120	32	
Package Size (Min)	45x32mm	37.5x34mm	15x15mm	

Unprecedented Capabilities and Optimization for Target Applications

Higher Performance
More Features and Capabilities
Increasing Logic Capacity
Greater IO Bandwidth

Lower Power
More Cost Optimizations
Less Logic Capacity
Smaller Form Factors

Source: Intel

Relevant SoM developments

intel

NVIDIA JETSON XAVIER SERIES

A **system-on-a-module (SoM)** that includes a GPU, CPU, and other peripherals.

A small, powerful **AI computer that can be used to run deep learning models on** underwater platforms.

Can specifically be used to:
- Identify target objects to perform manipulative operations,
- Create a segmentation network, and
- Design and implement the control system.

NX and AGX are the more powerful platforms that can run complex 3D object detection algorithms.

The **Tensor RT library** can significantly **improve the performance of 3D object detection algorithms** on Jetson platforms.

Tensor RT automatically **tunes the functions of deep neural networks, which can lead to significant speedups.**

	Nano	TX2	NX	AGX
AI Core	472 GFLOPs	1.33 TFLOPs	21 TOPs	32 TOPs
CPU	4-core Cortex A57	6-core Denver A57	6-core Carmel Arm	8-core Carmel Arm
GPU	128-core Maxwell	256-core Pascal	384-core Volta	512-core Volta
Memory	4 GB 64-bit LPDDR4	8 GB 128-bit LPDDR4	8 GB 128-bit LPDDR4	32 GB 256-bit LPDDR4
Size (mm)	100 × 80 × 29	50 × 110 × 37	100 × 90 × 32	105 × 105 × 65
Power	5 W (or 10 W)	7.5 W (or 15 W)	10W (or 15, 30 W)	10 W (or 15, 30 W)
Weight	100 g	211 g	184.5 g	670 g

Table 1. Specification of four NVIDIA Jetson platforms. NX and AGX are the more powerful platforms. Source: MDPI

Relevant System-on-Chip (SoC) developments

System-on-a-chip (SoC) designed for embedded vision applications.

The Myriad X can be used to **detect objects in real time, image classification, and natural language processing**.

Based on the **Intel Vision Processing Unit (VPU)** architecture and is manufactured using a **28nm process**.

The Myriad X **has a neural processing unit** (NPU) that can process **up to 10 TOPS**, and runs on as little as **1 watt of power**.

Figure 1. Movidius Myriad X VPU: Real-time DNN inferencing with 1 TOPS performance and 700Mpps image signal processing. Source: Myriad.

WSE-2 powers Cerebras CS-2 with **2.6 trillion** transistors, and **850,000 AI-optimized cores**.

Equipped with **40GB on-chip SRAM**, evenly distributed for single-clock-cycle access. **Outperforms GPUs** with **1,000x** capacity and **9,800x** bandwidth increase.

WSE-2's on-wafer interconnect delivers **220 Pb/s bandwidth**, erasing communication bottlenecks. Faster, **energy-efficient deep learning** compared to GPU clusters.

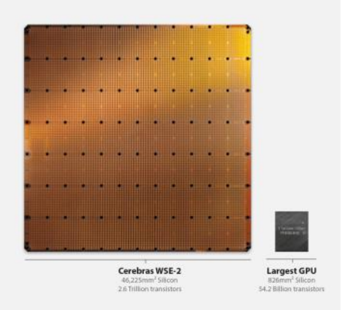


Figure 2. Cerebras WSE-2 is a 46,225mm² Silicon, with 2.6 Trillion transistors, compared to the largest GPU GPU, a 826mm² Silicon with 54.2 Billion transistors. Source: Cerebras.

Relevant Si photonic technologies

SiN platform for silicon photonics that can be easily **integrated** onto **SOI wafers**.
Si Photonics foundries **offer high bandwidths, low power consumption, and robustness to harsh environments**, which is required by Autonomous Underwater Platforms.

The Lumentum GaAs 53 Gbaud PAM4 driver IC is a **high-performance driver** that is optimized for **PAM4** modulation, **suited** for applications that require **high bandwidth and low inter-channel cross-talk**.

Lightmatter has produced 'The Passage', **a processing tower which works** with a universal silicon layer that **contains lasers, optical modulators, photodetectors, waveguides, as well as classical transistors** to accompany the logic.

PDK Devices	Performance
Edge Coupler	TE: <1.4dB/facet TM: <1.4dB/facet
Grating Coupler	≈ 4dB/facet
1X2 MMI 2X2 MMI 2X4 MMI	≈0.15dB ≈0.18dB ≈0.5dB
Polarization Beam Rotator & Splitter	TE <0.1dB, TM <0.2dB PER ~19dB

PDK Devices	Performance
O-Band, C-Band Ge Photodetector	BW: > 70GHz (C-Band), > 40GHz* (O-Band), R ~ 1A/W, Dark Current < 20nA
O-Band, C-Band High Speed MZM	EO BW> 40GHz 56GBaud
Thermal-Optical Phase Shifter	Power consumption <2 mW/Pπ
Crossing	<0.15dB, crosstalk <-40dB
APD	Please contact us for details

** O-band BW is limited by measurement tool capability*

Table 1. Process Design Kit specs. Source: AMF

Feature	Value
Bandwidth	53 Gbaud
Modulation	PAM4
Output voltage	Optimized for silicon and InP MZMs
TDECQ	Exceptional
Gain range	6 dB
Channel pitch	625- or 700-um
Inter-channel crosstalk penalty	4 dB better with 700-um pitch

Table 2. Specs for Driver for Silicon Photonics MZ Modulator to 56 Gbau. Source: LUMENTUM

40X waveguides in the space of one optical fiber.

800 + TPS Input/output bandwidth from each chiplet site for full reticle. And up to **250+ Tbp**s per chiplet site edge.

100X more bandwidth, and **<2NS Chiplet to chiplet latenc**y, single hop connectivity between every site.

Lightmatter Passage brings Co-Packaged Optics and Silicon Photonics to the Chiplet Era. Source: Lightmatter

TOOLS AND DATASETS

Highlighting tools and datasets for functional AI engine development.

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Expert Insight

The relevant AI engine for underwater applications is not specifically designed for the underwater environment. Instead, we can use models that are already available for over-the-water applications and adapt them to the underwater environment using transfer learning.

This is because developing complex and powerful AI networks is a very expensive and time-consuming process, and most of the resources are focused on making them work above the water. By using transfer learning, we can save time and money while still developing an AI engine that is effective in the underwater environment.

Dr. Marco Leonardi

Performance Analysis Engineer, ARM

Models developed in **academia & industry**

High-level control systems are responsible for the overall planning and execution of tasks.

Application	Description	Examples of applicability	Website
Robot Operating System (ROS)	A software development kit that provides a common platform for developing and deploying robot applications	• Design and implementation of AUV. • Optimizing the positioning and capturing of AUV recycling system. • Multi-Platform Obstacle Avoidance System for AUV.	ROS
Mission Oriented Operating Suite - Interval Programming (MOOS-IvP)	MOOS-IvP is a set of open source C++ modules for providing autonomy on robotic platforms, in particular autonomous marine vehicles.	• Autonomous control of autonomous underwater vehicle servicing platform. • An Autonomous Underwater Vehicle Dual Driver System. • Autonomous underwater acoustic localization through multiple unmanned surface vehicle.	MOOS-IvP
You Only Look Once (YOLO) v5.	YOLOv5 is a real-time object detection model that is applicable for recommendation systems and for standalone process management and human input reduction.	• Underwater animal detection. • Real-time sea cucumber detection. • Vision-based Deep Learning algorithm for Underwater Object Detection and Tracking.	YOLO v5
Single Shot MultiBox Detector (SSD)	An object detection platform that is known for its speed and accuracy. It can detect objects in a single pass through the image.	• Underwater Object Detection Based on Improved SSD with Convolutional Block Attention.	SSD

Advantages of YOLO v5 in Object Detection

YOLOv5

A one-stage detector that achieves higher accuracy and is faster than two-stage networks.

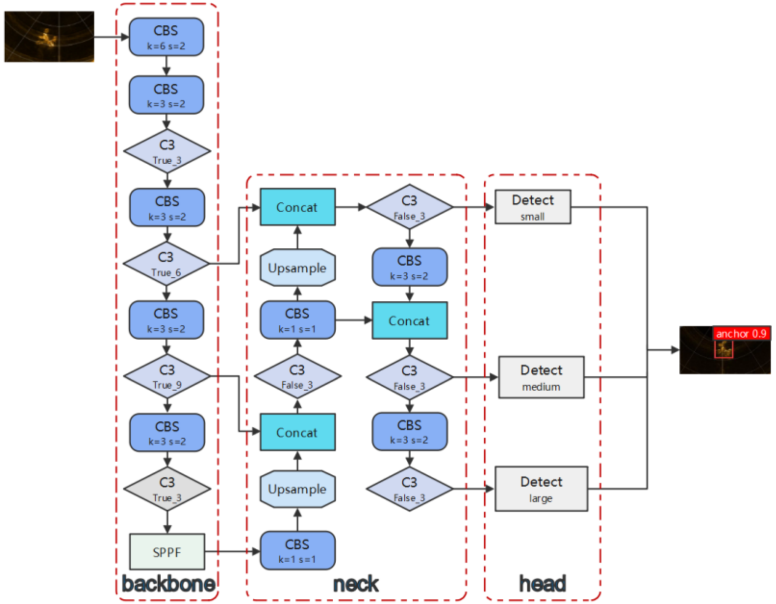
Uses improved **CSP DarkNet 53** as the backbone, **SPPF** instead of SPP, **FPN** and **PANet** to combine features at different scales, and **C IOU** loss as the loss function of the bounding box.

YOLO v5 is introduced as the basic **Convolutional Neural Networks**

The structure of YOLO v5 is **optimized to improve the performance of the detector for sonar images.**

The system **achieves a 1–3% increment of mAP which can be up to 80.2% with an average speed of 0.025 s (40 FPS)** in the embedded device.

The system has been verified and performs well both in the school tank and outdoor open water environments. Other advantages include the fact that it performs well and **meets the requirements of real time and light weight using limited hardware, though the system still faces difficulties when applied to real world underwater scenarios.**



YOLOv5 structure. The system is designed to be real-time, lightweight, and accurate. The proposed methods try to balance these three factors, but there are still some challenges. Research on model slimming, quantification, and distilling should be put forward to further improve the system. Source: Chen & Chen 2023

Control Models: Fuzzy Control, Neural Network Control, and Reinforcement Learning

AI platform Control System	Performance	Efficiency	Ease of Implementation	Strengths	Weakness
Fuzzy Control	Medium	Low	Medium	Robust to uncertainty and easy to understand	Not as accurate as other platforms, requires human expertise
Neural Network Control	High	Medium	Medium/High	Accurate, can be used for complex systems	More difficult to understand and implement in complex systems
Reinforcement Learning	High	High	Low	Learn from experience, can be used for complex systems	More difficult to implement, can be slow to learn

Table. Comparison of Control Models for AI Platform in Terms of Control Performance, Efficiency, Implementation Ease, Strengths, and Weaknesses

Fuzzy control is a good AI platform for systems where robustness to uncertainty and ease of understanding and implementation are more important than accuracy.

Algorithm	Class	Improvement	Control object	Control effect	References
Fuzzy control	Fuzzy Proportional Integral Derivative (PID)	Self-organizing fuzzy sliding mode control law	Path-following control of AUVs.	Track reference trajectories with a high degree of accuracy and robustness.	Taylor & Francis Online
		Possibilistic fuzzy C-means algorithm to diagnose thruster faults, and a fuzzy control strategy to recover from thruster faults.	Thruster fault diagnosis and fault tolerant control in AUVs	Fuzzy control strategy is improved by considering the uncertainty of ocean currents.	Mdpi
		Fault-tolerant control scheme	Find the optimal relationship between the linear extended states observer's parameters and tracking errors.	Estimate the fault, and the saturated sliding mode controller is used to ensure the stability of the system	IET research Online Library Wiley

Neural network control is a good choice for accurate systems, but it can be more complex than other platforms.

Algorithm	Class	Improvement	Control object	Control effect	References
Neural network control	Adaptive neural network	Lyapunov stability theorem and graph theory	Containment control	Effective containment control for multiple AUVs under time-varying constraints.	Science Direct
		Filtered technique	A visual docking controller for underactuated	Yaw and pitch angles, and a barrier	Online Library Wiley
		Saturated PID-type	Feedback-linearizing controller	Compensates NLIP uncertainties and disturbances.	Science Direct
		Neural network-based disturbance	Finite-time tracking error based on the dynamic sliding surface.	Adaptive observer-based dynamic sliding mode control for underwater vehicle.	Science Direct
	Online neural network controller	Dynamic Neural Control System	Compensate for unknown dynamics and external disturbances,	Track reference trajectories more accurately than a conventional feedback controller with no adaptive compensation.	Mdpi
		Proportional-Integral-Derivative control	Control strategy, but it requires the setting of control parameters.	Using the firefly algorithm to better control AUV motion.	IEEE xplore
	Hybrid control	Fractional sliding mode control and a compound control method.	Eliminates the chattering phenomenon without sacrificing the robustness of FSMC.	Robust against external disturbances.	Taylor & Francis Online

Reinforcement learning is a powerful AI platform that can be used to train agents to perform complex tasks in dynamic environments.

Algorithm	Class	Improvement	Control object	Control effect	References
Reinforcement Learning	Reinforcement learning	Designed the reward function	Precise trajectory tracking.	The thrusters were 11.14% less solicited by the latter controller.	IEEE xplore
	Deep reinforcement learning	A reward function for deep RL	Improve AUV trajectory tracking precise.	Effectively improve reliability and stability, reduce energy consumption, and restrain the vectored thruster sudden change.	Hindawi
	Interactive reinforcement learning	Learns from both human rewards and environmental rewards at the same time	Improve rewards and learning efficiency.	AUV can converge faster than a DQN learner from only environmental reward.	ARXIV
	Reinforcement learning	hybrid behavior coordination and SONQL to learn behavior state/action mapping	High-level control of autonomous underwater vehicles	Advantages using a competitive and cooperative behavior coordination, while SONQL is a new continuous approach to Q-learning that uses a multilayer neural network.	IEEE xplore

Models developed by the NASA Jet Propulsion Lab

These models are designed to function in extreme environments with limited connectivity, finding high applicability to underwater scenarios

NeBula is the latest modular software framework that enables robots to autonomously explore unknown and challenging environments under uncertainty.

NeBula (Networked Belief-Aware Perceptual Autonomy) is one of the most recent NASA Jet Propulsion Laboratory development. NeBula has the potential to achieve the following features:

Verifiable autonomy under extreme conditions: NeBula develops an autonomy architecture that translates the mission specifications into single- or multi-platforms behaviors. It quantifies risk and trust by taking uncertainty in platform motion, control, sensing, and environment into account.

Modularity and mobility-based adaptation: NeBula focuses on a modular design to enable adaptation to various mobility platforms and computational capacities.

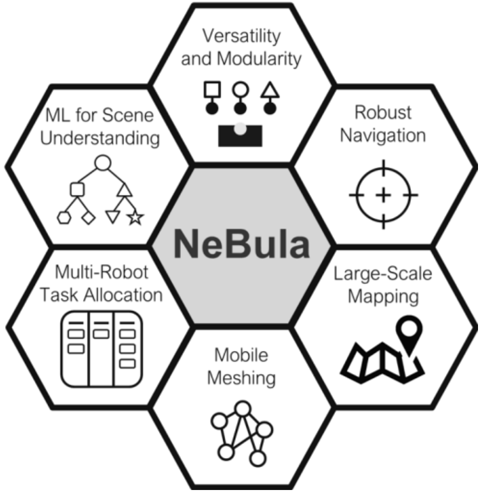
Resilient navigation: NeBula develops a GPS-free navigation solution resilient to perceptually-challenging conditions. It relies on degeneracy-aware fusion of various sensing modalities, including vision, IMU, lidar, radar, contact sensors, and ranging systems.

Single- and multi-robot SLAM and dense 3D mapping: NeBula develops GPS-denied large-scale SLAM solvers and 3D mapping frameworks using confidence-rich mapping methods. It provides precise topological, semantic-based, and geometrical maps of extreme environments.

Extreme traversability: NeBula develops solutions that have enabled robots to autonomously traverse extreme terrains. It can handle loose and slippery surfaces, muddy terrains, rock-laden terrains, high-slope areas, and stairs.

Multi-platform operations and mesh communication: NeBula can be implemented on multi-robot systems to enable faster and more efficient missions. It can also create a wireless mesh network backbone using static radios.

Autonomous skill learning: NeBula applies and extends reinforcement learning and machine learning methods to enable fast and safe robot motions in perceptually-degraded environments.



NeBula is a promising new technology that has the potential to revolutionize the way we explore extreme environments. It is a powerful tool that can help robots to safely and efficiently navigate through unknown and dangerous terrain. Source: NASA Jet Prop Lab.

Model-driven engineering and domain-specific languages (DSLs) proven useful in the development of complex systems with extensive applicabilities

Application	Description	Examples of applicability	Website
CARACaS (Control Architecture for Robotic Agent Command and Sensing)	CARACaS is an architectural pattern developed at NASA in 2011 for control of autonomous underwater vehicles (AUV) and autonomous surface vehicles (ASV).	• Control Architecture for Robotic Agent Command and Sensing.	CARACaS
CLARAty (Coupled Layer Architecture for Robotic Autonomy)	CLARAty is a modular and adaptable architecture developed at NASA, and has been used in a variety of applications, including planetary surface-exploration rovers, underwater vehicles, and search and rescue robots.	• The CLARAty architecture for robotic autonomy. • Claraty: A collaborative software for advancing robotic technologies. • Improved CLARAty Functional-Layer/Decision-Layer Interface.	CLARAty
CASPER (Continuous Activity Scheduling Planning Execution and Replanning)	CASPER is a system that enables fast and continuous planning designed for spacecrafts. This makes it possible to control the vehicle in real time, even in remote and dangerous environments.	• Casper: Space exploration through continuous planning. • Autonomous planning and scheduling on the TechSat 21 mission. • Using Iterative Repair to Improve the Responsiveness of Planning and Scheduling.	CASPER
Onboard autonomy, Multi-rover coordination, and Planning, Scheduling and Execution.	Robots need to explore unknown areas in real time and avoid obstacles, without loosing their communication systems. Within the system robots need to be able to communicate with each other using other methods, such as lasers or acoustic waves.	• Copilot MIKE: An Autonomous Assistant for Multi-Robot Operations in Cave Exploration. • One Operator to Rule Them All: Human-Robot Interaction for Real-World and Analog Subsurface Exploration. • Supervised Autonomy for Communication-degraded Subterranean Exploration by a Robot Team.	Rovers autonomy

Data for training AI models to enable underwater autonomy

Recommended by PreScouter SMEs

"AI and ML algorithms require large amounts of data to train. This data can be expensive and time-consuming to collect, label, and annotate. Additionally, the data may be noisy or biased, which can affect the accuracy and reliability of the models.

However, open source data centers are using AI to process information relevant for ML for Autonomous Underwater Platforms.

Dr. Marco Leonardi

Performance Analysis
Engineer, ARM

Representative costs for labeling relevant data: Images

When assembling training sets, various factors affect training label availability per class. Labeling speed varies on approach:

- whole image classification is swift (e.g., ~5 seconds/image)
- instance segmentation is slower (~13.5 seconds/image)
- panoptic labeling is slowest (up to ~20 minutes/image).

At an average labeling speed, 1,000 images take ~3.75 hours to label. **For a dataset akin to Parks Canada's (47,279 images, 55 classes), around 21 full workdays are needed**.

1,000 images → take ~3.75 hour

In Katija et al.'s (2022) review of **Fathom Net**, over 2,000 hours (~$165,000) were spent annotating about 66,000 images, at an average cost of $2.50/image.

60,000 images → over 2,000 hours → ~$165,000 ($2.50/image)

Extrapolating this to the 10-100 TBs of data required to train autonomous systems, the cost can range from **$5M-10M** (assuming 4MB/image).

4MB image → 10-100TBs data → $5M-10M cost

Constructing labeled datasets demands substantial resources, especially for detailed annotations. This underscores well-annotated data's value in advancing machine learning research and applications.

Leveraging SONAR data for autonomy

The average data size for sonar data can vary significantly depending on factors such as:

- the type of sonar system used
- the specific application
- the duration of the data collection
- the sampling rate.

A rough estimate for SONAR data size might be in the range of several gigabytes to tens of gigabytes per hour of data collection. For instance, high-resolution multibeam sonar systems used for seafloor mapping can generate large datasets due to their detailed imaging capabilities. On the other hand, single-beam sonar systems used for navigation and obstacle avoidance might produce smaller datasets.

A 2022 publication in the Journal of Marine Science and Technology highlights some of the key issues with leveraging SONAR data, namely:

- The number of sonar images is far less than that of optical images
- The few-shot training of a deep network is more difficult
- The problem of overfitting is more prominent

ResNet-ACW, a novel network, was developed using a diverse dataset of SONAR images from various devices like sidescan, forward-looking, and 3D imaging SONAR. It achieved a remarkable 95.93% accuracy, yet applying it to real-world SONAR data faces challenges such as turbidity and shadows, affecting accuracy for automated processes.

Synthetic-Aperture SONAR (SAS) Sensors & Data Storage:

- SAS sensors produce large data (1 GB/hour).
- Storage needs depend on sensor type (e.g., side-scan, forward-looking).
- Cameras add to storage requirements.
- AUV's mission can generate ≈ 20 GB data/hour of mission.

"In the realm of signal processing, there isn't a specific set of AI algorithms or tools exclusive to this domain. Instead, researchers and developers are actively engaged in the application of AI algorithms, particularly those used in computer vision, which are being adapted/repurposed for use in SONAR-based applications.

Anonymous Interviewed Expert

Open source data centers that collect large multi-modal sensor data set for mobile robotics research in the marine domain.

Examples

VIAME

CORALNET
A WEB SOLUTION FOR CORAL REEF ANALYSIS

FATHOMNET

BCO-DMO
Biological & Chemical Oceanography Data Management Office

NORCE

MBARI
Monterey Bay Aquarium Research Institute

Sea Grant
MIT

IMAGE DATA

VIDEO DATA

SENSOR DATA

LABELED DATA

Using AI to Process Ocean Imagery helps to address some of the Labeled data problems

1. **Labeled data is scarce for new or emerging applications**, making it difficult to train accurate and reliable machine learning models.
2. Labeling data is **expensive**, especially for complex or time-consuming tasks.
3. **Quality** of labeled data can be affected by the biases of the people who label it.
4. It can be **difficult to scale up the labeling process** to meet the needs of large datasets.

Additional resources for developing relevant AI algorithms: Image classification

Image Enhancement, Color Correction/Restoration

1. **EUVP dataset**: Data, Paper, Code. (paired and unpaired data; FUnIE-GAN)
2. **Underwater imagenet**: Data, Paper, Code. (paired data; UGAN)
3. **UIEBD dataset**: Data, Paper, Code. (Water-Net)
4. **SQUID dataset**: Data, Paper, Code. (Underwater-HL)
5. **U-45**: Data, Paper. (UDAE)
6. **RUIE benchmark**: Data, Paper. (RUIE-Net)
7. **Jamaica port royal**: Data, Paper, Code. (Water-GAN)
8. **Virtual periscope**: Data, Paper.
9. **Color correction**: Data.
10. **Color restoration**: Data, Paper, Code.
11. **TURBID data**: Data, Paper.
12. **OceanDark dataset**: Data, Paper.

SISR: Single Image Super-Resolution

1. **USR-248**: Data, Paper, Code. (for 2x, 4x, and 8x training; SRDRM, SRDRM-GAN)

SESR: Simultaneous Enhancement and Super Resolution

1. **UFO-120**: Data, Paper, Code. (for 2x, 3x, and 4x SESR and saliency prediction; Deep SESR)

Image Segmentation

1. **SUIM**: Data, Paper, Code. (SUIM-Net)
2. **Coral-Net**: Data, Paper, Code. (Coral-Seg)
3. **Eilat dataset**: Data, Paper.
4. **Change detection**: Data, Paper.

Additional resources for developing relevant AI algorithms: Object detection & Classification

General

1. **MOUSS data**: Data. (CVPR 2018 workshop challenge)
2. **MBARI database**: Data.
3. **HabCam database**: Data.
4. **OUC-vision**: Paper.
5. **MARIS project**: Data.
6. **NOAA data**: Data.
7. **Aqualoc dataset**: Data, Paper. (visual-inertial-pressure localization)
8. **Brackish dataset**: Data, Paper.
9. **SUN database** (underwater scenes): Data.
10. **FathomNet** (image database): Data.

Human-robot cooperation

1. **Diver detection**: Data, Paper.
2. **Robot tracking by detection**: Data, Paper.
3. **CADDY diver pose data**: Data, Paper.

Coral-reef

1. **Moorea corals** (UCSD): Data, Paper.
2. **Coral-reef Puerto Rico**: Data.
3. **Coral-Net**: Data.

Coral-reef

1. **Moorea corals (UCSD)**: Data, Paper.
2. **Coral-reef Puerto Rico**: Data.
3. **Coral-Net**: Data.

Fish

1. **WildFish database**: Data, Paper.
2. **Labeled fishes**: Data, Paper.
3. **Fish4Knowledge data**: Data.
4. **Fish databas**e: Data.
5. **AQUALIFEIMAGES database**: Data.
6. **Rockfish**: Data.
7. **Fish recognition data**: Data, Paper.
8. **Oceanwide images**: Data.
9. **Fish detection and tracking**: Data, Paper.
10. **Fish trajectory detection**: Data, Paper.

Trash and marine debris

1. **TrashCan**: Data, Paper
2. **Trash-ICRA19**: Data, Paper
3. **Deep-sea debris database**: Data, Paper.
4. **Tiny plastics posing threat to turtles**: Data, Paper

Additional resources for developing relevant AI algorithms: Acoustic, stereo, docking, and temperature data

Acoustic Data

1. **Five-element acoustic dataset**: Data, Paper.
2. **DIDSON dataset**: Data1, Data2, Data3, Paper. (fishery classification and assessment)
3. **Spectrogram Analysis**: Data, Paper.
4. **Caves sonar and vision data**: Data, Paper.

Stereo Data

1. **Tasmania coral point, Scott reef-25, O'Hara-7**: Data, Paper.
2. **Stereo from Flicker**: Data, Paper.
3. **CADDY stereo data**: Data, Paper.
4. **HIMB data for UW StereoNet**: Data, Paper. (UW-StereoNet)
5. **SQUID dataset**: Data, Paper

Docking Data

1. **Underwater Docking Images Dataset(UDID)**: Data, Paper.

Temperature Data

1. **Underwater temperature dataset**: Data.

All the lists provided include direct links to data available and research papers.

RELEVANT DEVELOPMENTS

Highlighting concrete real world examples of relevant developments in this space.

World's top Research Institutes and Top Researchers working in the development of Autonomous Underwater Platforms*

MASSACHUSETTS INSTITUTE OF TECHNOLOGY (MIT)

The University has **the Sea Grant-AUV Lab**, which focuses in the development of multimodal sensor fusion, machine vision, and marine datasets. MIT AUV Lab partners with Lockheed Martin to enhance EMATT submarine vessel through algorithm development and the use of biomimetics.

Top MIT Researchers:

Michael Benjamin: Head of the The Computer Science and Artificial Intelligence Lab (CSAIL) at MIT. He established moos-ivp.org at MIT and focuses on autonomous marine vehicle algorithms and software development.

John Leonard: Research interests include navigation and mapping for autonomous mobile robots, long-term visual simultaneous localization and mapping in dynamic settings, and self-driving cars.

*According to PreScouter SMEs

UNIVERSITY OF HAIFA (ISRAEL)

The Hatter Department of Marine Technologies develops novel methods and advanced equipment for applied research of the sea.

The university harbors the MARINE IMAGING LAB (VISEAON).

The research facility is focused on creating cutting-edge optical imaging technology and advanced computer vision techniques (i.e., Imaging, Submerged Sensing, Ocean Engineering, Machine Vision, Computational Photography). The lab developed SeaErra-Vision, developing intelligent vision solutions for the underwater world.

Top MIT Researchers:

Morel Gropes: Head of the Subsea Lab. The Lab specializes in developing the state-of-the art technologies for unmanned marine vehicles in propulsion, manoeuvring and control as well as in Seaway planing craft motion, autonomous speed control, marine vehicle modeling, floaters, deep-sea propulsion, pressure vessels.

World's top Research Institutes and Top Researchers working in the development of Autonomous Underwater Platforms *(cont'd.)*

CNR ISMAR ISTITUTO DI SCIENZE MARINE (ITALY)

CNR ISMAR is developing and testing cutting-edge marine technologies, including autonomous underwater vehicles (AUVs), remotely operated vehicles (ROVs), and other robotic systems for underwater exploration and data collection.

Seebyte (UK)

SeeByte offers software solutions for uncrewed maritime systems. Our open architecture technology provides enhanced capability, autonomy, and value to maritime systems and their users. This is key in providing the needed simulations.

Nanophotonics for light detection and ranging technology

LiDAR is a crucial sensor technology for autonomous vehicles, artificially intelligent robots, and unmanned aerial vehicle reconnaissance.

Novel nanophotonic platforms could overcome the hardware restrictions of existing LiDAR technologies.

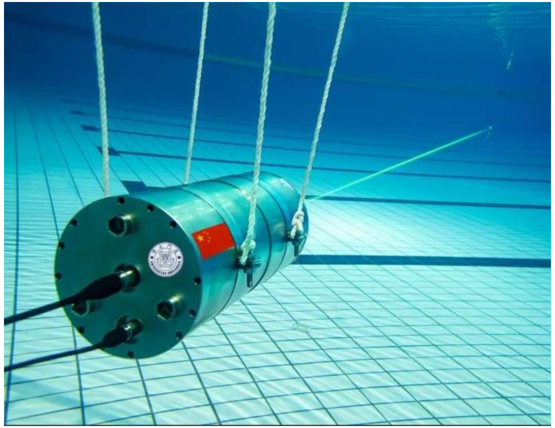
Nanophotonic approaches such as integrated photonic circuits, optical phased antenna arrays, and metasurfaces have demonstrated exceptional functional beam manipulation properties.

Metasurfaces are expected to disrupt modern optical technologies and are being incorporated into commercially viable, fast, ultrathin, and lightweight LiDAR systems.

Lumotive is developing an ultra-compact solid-state LiDAR system using metasurfaces. The system can scan a 1D frame at 25μs and has a 120° FOV. However, it only supports 1D scanning and has a relatively low FOV.

Samsung has developed a similar system using metaphotonic SLMs. The system can scan a wider angle (8°) but has a lower diffraction efficiency (1%). It also consumes more energy (283 fJμm^{-2}).

Both systems have the potential to be used in LiDAR applications. However, they still have some limitations that need to be addressed.



A new lidar system that uses just 1 microjoule of pulse energy and 22.4 millimeters of receiver aperture was developed by researchers. The entire system is 40 centimeters long and 20 centimeters in diameter, and it can operate up to 1 kilometer underwater (up to 1000 m depth). To improve sensitivity, the researchers incorporated single-photon detection into their compact underwater Raman lidar system. Source: Xiamen University.

Avoid losing communication systems in unpredictable environments I

Robots need to explore unknown areas in real time and avoid obstacles, **without loosing their communication systems**. Within the system robots need to be able to communicate with each other using other methods, such as lasers or acoustic waves.

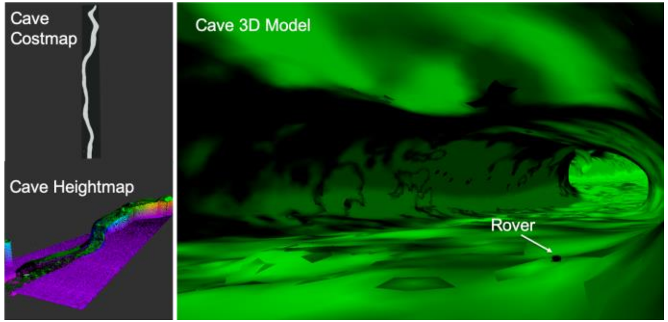
There are two AI-based proposals

COORDINATION STRATEGIES

Dynamic Zonal Relay Algorithm with Sneakernet Relay: Rovers are first distributed to designated zones along the cave. Each rover takes science data in its zone and transmits it to the base station. If a rover is no longer operable, the other rovers redistribute the zones. Rovers can then acquire science data further into the cave and transfer it out using sneakernet relay.

This algorithm ensures that rovers are able to communicate with each other and transmit data back to the base station. It is efficient, robust, and adaptable to changing conditions.

Scout Observation Algorithm: A set of scout rovers with limited science capability explore the cave using a method such as the Dynamic Zonal Relay Algorithm to find science targets, which are then visited by a more powerful science rover. The data collected by the science rover is then relayed out to the base station using the scout rovers.



Simulation visualization. The combination of uncertain communication and limited mission duration suggests that accounting for energy when transmitting data out of cave-like structures would be beneficial to mission success. AI could be used to develop energy-aware, smart, distributed routing capabilities in a multi-rover exploration scenario. This would allow rovers to map and explore caves more efficiently and effectively. Source: NASA Jet Prop Lab.

Avoid losing communication systems in unpredictable environments I (cont'd.)

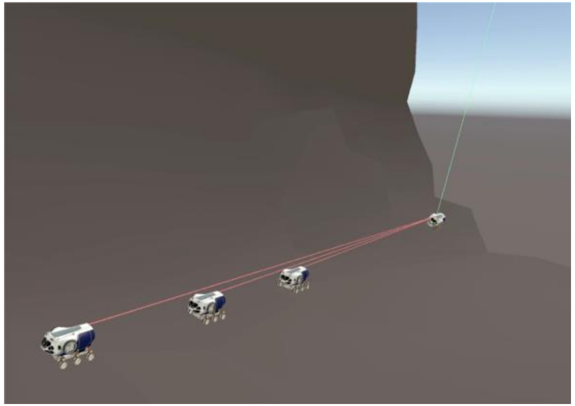
ENERGY AWARE DATA ROUTING

Energy-Aware Contact Graph Routing: This algorithm extends traditional CGR by finding paths of minimal energy over a time-varying topology of pre-scheduled contacts.

These coordination strategies and energy-aware data routing techniques are applicable across a wide range of caves and underground structures, as well as **unknown target environments in which communication is limited or not available**.

NASA has also developed a simulation framework to easily run different configurations for mission concepts. This framework provides diagnostic output to evaluate performance, including an interactive visual playback of the scenario, activity timeline and distribution, paths travelled by the assets, and energy usage distribution.

This work is an important step towards the development of autonomous multi-rover systems for cave exploration. The proposed coordination strategies and energy-aware data routing techniques can help rovers to explore caves more efficiently and effectively, even in challenging environments with limited communication.



Visualization of rovers exploring a cave. Cave model courtesy of Tommaso Santagata/Inside the Glacier Project; Rover 3D model, a notional Space Exploration Vehicle (SEV), from NASA LaRC Advanced Concepts Lab, AMA Studios. Source: NASA Jet Prop Lab.

Avoid losing communication systems in unpredictable environments II

Due to the communication paradigm associated with operating an underwater submersible, the vehicle must be able to act autonomously when achieving specific goals.

NASA is focused on performing autonomous science, the localization of features of interest with limited to no human interaction.

In 2017-2018, an autonomous nested search method for hydrothermal venting was developed and tested in simulation using a hydrothermal plume dispersion model developed by Woods Hole Oceanographic Institution.

Researchers have developed a fully autonomous nested search strategy for the localization of hydrothermal vents on oceanic environments.

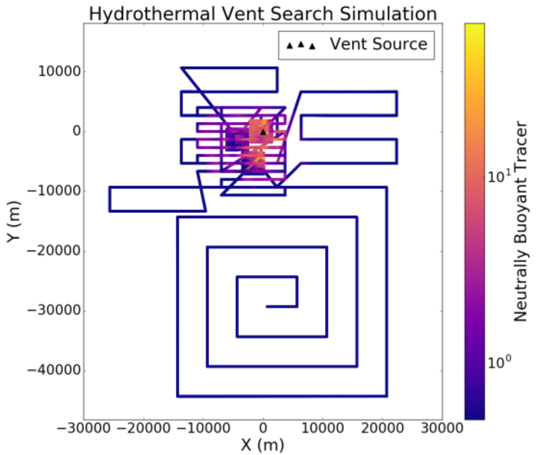
This strategy is based on a **manual three-phase nested search**.

The strategy was tested using a hydrothermal plume dispersion simulation developed by Woods Hole Oceanographic Institution using FVCOM, an existing ocean circulation model.

The results of the simulation show that the strategy is effective in locating hydrothermal vents.

This research is important because it could help us to explore ocean worlds more efficiently and effectively.

By enabling autonomous submersibles to search for hydrothermal vents, this research will allow us to explore ocean worlds more quickly and without the need for human intervention.



Simulation visualization. Simulation showing the observed plume strength during the nested search to locate the hydrothermal vent at (0,0). The simulated vehicle performs surveys of repeatedly higher resolution until the vent source is found. Source: NASA Jet Prop Lab.

IP LANDSCAPE ANALYSIS 2003–2023

Exploring the IP space of AI/ML/DL for underwater autonomy.

An analysis of IP applications reveals a robust upward trend, underscoring the rapid surge in the development of technologies that support autonomous underwater platforms.

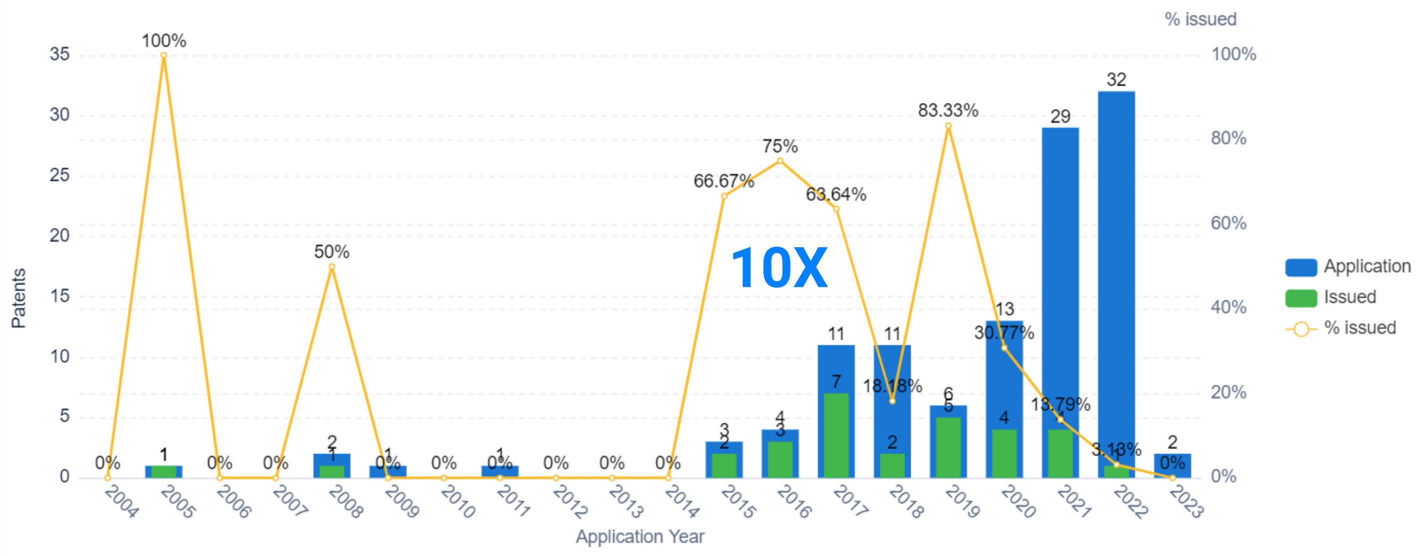


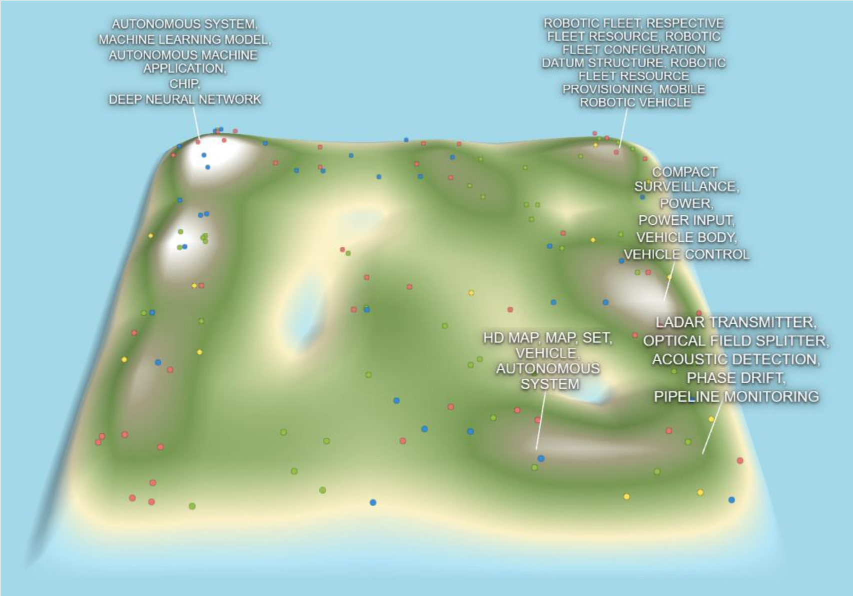
Figure. Relationship between number of patents and corresponding years, highlighting trends in innovation and intellectual property activity.

The IP landscape encompasses a wide array of applications, including surveillance and unmanned vehicles, intricate sensor integration and fusion techniques (acoustic drift and LADAR). Pivotal strategies for achieving autonomy rely through advancements of specialized chips and deep neural networks.

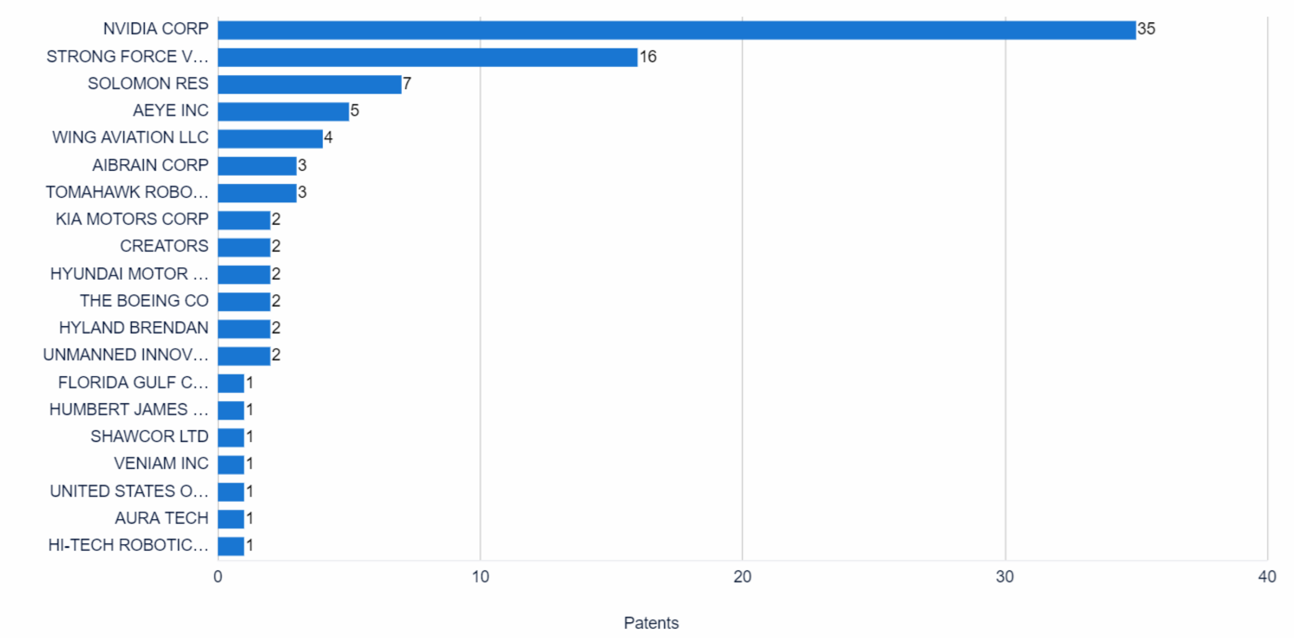
The Technology Landscape visualises the layout of the technology space, with peaks representing more concentrated area of patenting activity and troughs representing areas of little or no activity - these suggest areas of potential opportunity and exploration.

Legend

Patents published in 2023 (42 patents)
Patents published in 2022 (32 patents)
Patents published in 2021 (12 patents)
Patents published in 2020 and before (41 patents)



NVIDIA has filed the most patents in the past 4 years in the field of autonomous underwater platforms.



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Technical Director

Sofiane earned his B.S. in Materials Science and Engineering from The University of Illinois at Urbana-Champaign, and his PhD in Materials Science and Engineering from the Georgia Institute of Technology, where his research focused on nanotechnology and energy storage. Before joining PreScouter, Sofiane worked as an emerging technology and business strategy consultant. He specializes in the high tech and aerospace and defense sectors, in addition to working closely with private equity and venture capital clients. Sofiane is based in Paris, France.

Jorge L. Hurtado, PhD

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Jorge, a Research Analyst and Editor Assistant at PreScouter, helps provide clients with high-quality information and analysis on disruptive technologies, aiding companies in finding new markets and staying competitive. He holds a MA in conservation and development, a PhD in Biology and Statistics, and a diploma in Green Economy from the University of Florida, Syracuse University, and Toronto Metropolitan University, respectively. Jorge is based in Toronto, Canada.

PRESCOUTER EXPERTS

PreScouter Subject Matter Experts (SMEs) interviewed to provide insights featured in this Intelligence Brief

Dr. Marco Leonardi

Performance Analysis Engineer, ARM

Dr. Leonardi is an AUV expert with a focus on image processing and machine learning. He has a keen interest in AUV automation, deep learning, real-time systems, A.I, and robotics. He is also the founder of Exmarte AS, developing human-in-the-loop remote driving tech for entertainment.

Anonymous SME

Autonomy & Data Science

This AUV expert is a prominent figure in the field. With extensive experience in AUV design and operation, they've made significant advancements, including groundbreaking algorithms for motion planning and innovative visibility analysis techniques for complex environments. They're recognized for their insights into marine robotics and have diverse research interests spanning motion planning, 3D visibility analysis, navigation, and trajectory planning for USVs and UUVs, cooperative decision and control, and sensor-based navigation. Currently, they're spearheading the development of an advanced AUV navigation system, pushing the boundaries of underwater technology for commercial and defense applications.

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